THE IMPACT OF COMMUNITY CURRENCY PROGRAMS IN KENYA

CS112 SPRING 2019 FINAL PROJECT
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INTRODUCTION

Grassroots Economics (GE) is a non-profit organization that has piloted 9 community currency programs across Kenya, onboarding more than 1,000 small businesses since its creation in 2010. A community currency (CC) is a complementary medium of exchange to a national currency that draws on the strength of financial and social networks in order to stimulate local economic activity with some social or environmental objective in mind. Vouchers, either in physical paper or, more recently, digital form, are issued and honoured by every member of the network, and can only be spent on goods and services from other members – in other words, local business owners. Therefore currency circulation relies on mutual acceptance and is backed by the informal resources of the community. (Bendell et al., 2015).

GE claims that the majority of its participants are women and that its programs across a number of Kenyan slum communities have stimulated local business growth and social cohesion. This paper discusses how statistical methods can be used to evaluate these claims and draw nuanced interpretations based on observed data from a 2017 baseline survey. GE's community currency program is based on self-selection; therefore statistical methods are employed to answer the research question, "What kind of impact does a community currency program have on participants and is this impact externally valid?"

METHODOLOGY

1. Data Selection

GE's 2017 baseline survey was conducted by 29 field workers who approached 1,383 respondents in-person and allowed them to input their answers on a mobile device. The survey contained over 71 questions dealing with demographic, behavioural, and evaluative variables, with a mix of differential scales (Likert-type and semantic) and qualitative questions (multiple-choice, dichotomous, and open-ended). Most answers were numerically encoded and could thus be interpreted as binary or categorical variables for the purposes of statistical regression. 38.05% of respondents (530 people) were CC users (treatment) and 61.95% of respondents (863 people) were non-CC users (control). 54% of all respondents were women and within the treatment group, 58% were women.

In order to answer the proposed research question, survey data was reduced to the following 21 questions that reflect variables considered relevant by mainstream literature on the topic:

Variable Name	Survey Question
type	Has Community Currency Been introduced in this location?
cc_name	Name of Community Currency being used in area.
years_in_area	How many years have you lived in ${community}?
age	How old are you today?
gender	What gender are you?
educ_level	What is the highest level of schooling you have obtained?
civil_status	What is your marital status?
fin_status	Think about your financial situation. Would you describe yourself as:
muni_support	In the last 1 year, has the government provided you with any support that has enabled you to live a better life?
forced_to_consult	I am forced to consult other people when I have to make decisions
bank	Do you have a bank account?
income_source	What have been the sources of income for your whole household over the last year?
income_total	Considering the income from ALL of your jobs, how much income did you bring home in the last month in KSH?
income_total_cc	Considering the income from ALL of your jobs, how much income did you bring home in the last month in ${cc_name}?
own_business	Do you own your business premise?
sales_increase	What has been the effect of using ${cc_name} on sales?
food_daily_ksh	How much do you spend on food and drink daily in KSH?
food_daily_cc	How much in ${cc_name} do you spend on food and drink daily?
students_cc	How many students do you support using ${cc_name}?
gift_cc	Over the last one month how much did you give in ${cc_name} to support people or groups without expecting compensation?
benefit	What has been the biggest benefit of using ${cc_name} in ${community}?

Table 1: 2017 baseline survey questions selected for statistical methods

2. Justification for Statistical Methods

Most impact evaluation research conducted on GE's programs lacks a statistical evidenced-based approach. For example, in the most recent exhaustive list of research papers on GE's website, only 2 out of 13 papers conduct statistical matching of some kind, and both rely on propensity score matching (Sillen, 2017; Cauvet, 2018). While propensity score matching prunes data just as well as other methods, it still performs poorly in identifying the difference between true treatment and control when tested against real experiments (King and Nielson, 2019). In other words, propensity score matching increases model dependence and bias. This is important for statistical credibility and effective program evaluation in a context where conducting a full randomized control trial is not yet practical or financially feasible. This paper employs genetic matching which is an evolutionary search algorithm used to determine the weight each covariate is given in order to improve overall matching balance (Diamond and Sekhon, 2013). Conditions for a Stable Unit-Treatment-Value Assumption (SUTVA) are satisfied because there is only one form of treatment (participating in the community currency program) and there is no direct interference amongst units whereby the treatment or control state of one affects the treatment or control state of another.

A note on the choice of the outcome variable is also important. Community currencies are a nascent field of research and literature varies on the motivation for the model. This means that outcomes such as altruism, community trust, income, school attendance, or food security can either be seen as direct outcome or byproduct of community currency programs, depending on the developmental focus of the organization conducting those programs. GE is founded on the belief that alternative currency creation stimulates local economic development – specifically resource productivity and resilience. This study, therefore, looks at the total monthly income between community currency users and non-community currency users 7 years after the initial implementation of the program. Because this is a retrospective observational study design, a sensitivity analysis is used to determine any hidden bias that would obscure qualitative conclusions (Rosenbaum, 2005).

3. Genetic Matching

Covariates used in statistical matching were selected according to how well they determine program participation. Figures 1-4 below visualize the distributional difference of covariates between treatment and control groups. Table 2 shows the results of a logistic regression that was used as an additional guide to determine which covariates ought to be included in genetic matching.

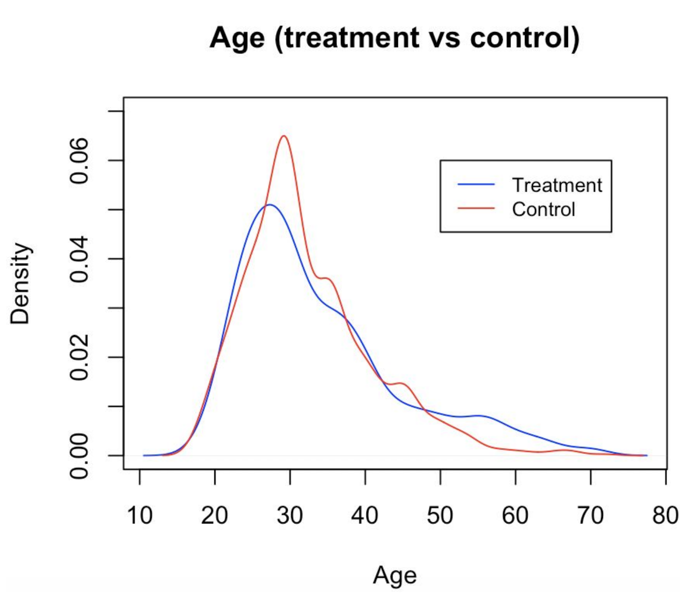

Fig. 1: Age distribution between treatment and control

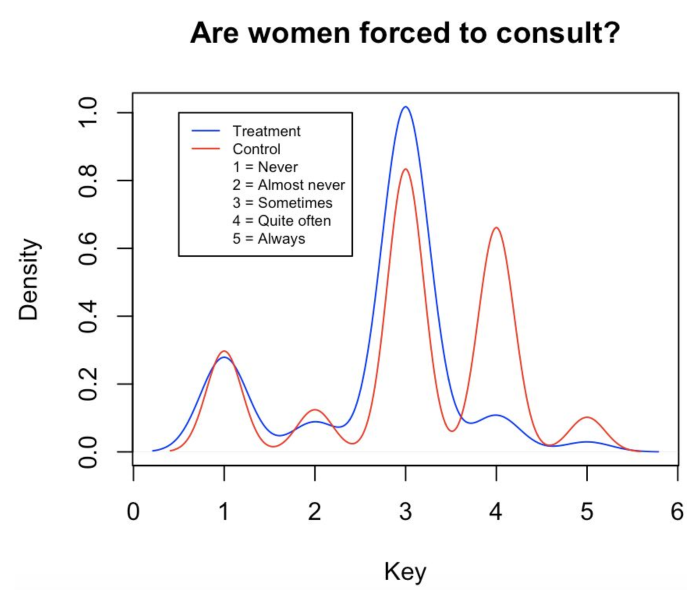

Fig. 2: Female decision making between treatment and control

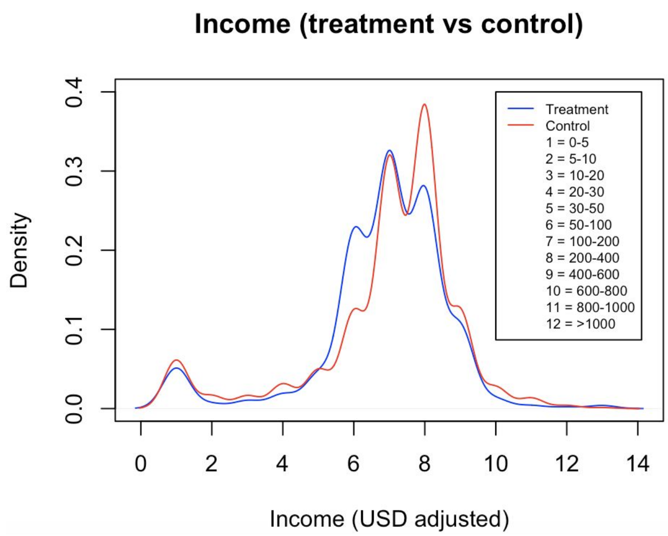

Fig. 3: Monthly income between treatment and control

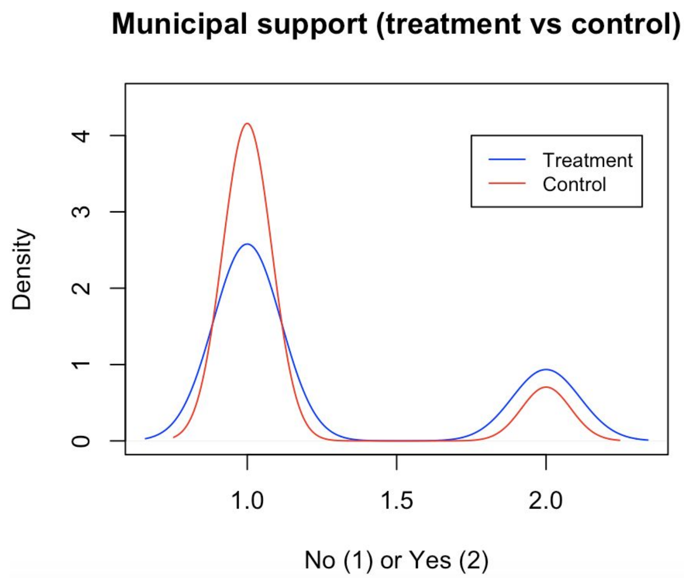

Fig. 4: Municipal support between treatment and control

Covariate	Coefficient estimate	Standard error	p-value
Intercept	-0.658582	0.529645	0.213706
Years in area	-0.023676	0.007374	0.001325 **
Age	0.028498	0.007524	0.000152 ***
Gender	0.214723	0.123312	0.081632 .
Education level	0.426362	0.078438	5.46e-08 ***
Civil status	0.044997	0.032038	0.160172
Financial status	-0.793756	0.080496	< 2e-16 ***
Municipal support	1.241461	0.171494	4.52e-13 ***
Forced to consult	-0.405855	0.061803	5.14e-11 ***
Bank ownership	-0.140171	0.144734	0.332808
Business ownership	0.150603	0.165986	0.364236

Table 2: Logistic regression results for propensity score. Years in the area, age, gender, education level, financial status, municipal support and decision making significantly determine whether a subject is assigned to treatment or control.

*Significance codes: 0 = ***, 0.001 = ** , 0.1 = *, 0.05 = .*

The genetic matching results in Table 3 dropped 197 treatment observations to achieve matching between covariates in treatment and control units. The only covariate that could not be matched to reduce statistically signifianct differences between treatment and control was number of years lived in the area.

	Covariate mean				**T-test p-value**	
	Before matching		**After matching**		**Before Matching**	**After matching**
	Treatment	**Control**	**Treatment**	**Control**		
Years in area	10.892	12.584	9.1411	8.7598	0.002118	0.04724
Age	33.987	32.378	31.423	31.423	0.0038509	0.42633
Gender	1.5868	1.5272	1.5435	1.5435	0.029574	1
Education level	3.7906	3.5933	3.9099	3.9099	4.741e-05	1
Civil status	N/A	N/A	N/A	N/A	N/A	N/A
Fin. status	3.3226	3.7323	3.5976	3.5976	2.2204e-16	1
Municipal support	1.266	1.1448	1.2432	1.2432	1.0958e-07	1
Forced to consult	2.7019	3.0324	2.6847	2.6847	4.3365e-09	0.34582
Bank ownership	1.6415	1.6559	1.7147	1.7147	0.58695	1
Business ownership	N/A	N/A	N/A	N/A	N/A	N/A

Table 3: Results of genetic matching with replacement. pop. size=1000, max.generations=10, wait.generations=2, caliper=1

DECISION MEMO

Date: April 24, 2019

To: Galia Bernatizi, Cofounder of the Bancor Protocol

From: Rebecca Mqamelo, Social Impact Research Lead for the Bancor Foundation

Subject: Mixed Success of Grassroots Economic Program

Executive Summary

Bancor recently partnered with Grassroots Economics (GE) in Kenya in order to integrate community currencies away from physical paper to a decentralized blockchain network. This decision memo is the first of a series of impact evaluation reports aimed at tracking the success of the Bancor partnership. Before digitalizing the program, GE operated for 7 years in a number of Kenyan communities. Statistical results point to mixed success. On the one hand, participants who self-select to take part in the commuity currency program can expect to earn lower than non-participants. On the other, GE's success may lie in its effect on social capital within communities. How we evaluate these mixed results ultimately rests on the objectives and value proposition we set as the basis for the community currency program. The recent migration to a digital network makes these initial results a useful baseline to use as a comparison for future impact evaluations.

Statistical Results

Before matching, the minimum p value between treatment and control was effectively zero (2.22e-16). After matching, the minimum p value was 0.002. This means that even genetic matching with replacement could not reduce the differences between treatment and control; the difference between the two groups is too statistically significant to ignore. Matching with a caliper of 1 (a maximized standardized difference of 1 between covariates for matched treatment and controls) resulted in 197 treatment units being dropped. Furthermore, the sample average treatment effect for the treated units was -0.56757, meaning that participants of the community currency program can expect to earn a lower income than those who do not. Translating this result in relation to the 1-13 categorical income scale, this roughly equates to a monthly income that is 5,000 kenyan shillings (or $50) lower than non-participants of the program. However, a Rosenbaum Sensitivity Test revealed that this result was neither statistically significant nor credible because a gamma of 1 had a minimum p value bound of 0.5.[1]

From a study design perspective, these poor results are not surprising considering that participation for treatment is based on self-selection. The coice of income as an outcome variable is always risky considering that community currencies are not the only source of income for a person or business owner, although they may enhance existing avenues for income. In other words, unobserved confounding variables are inherent to the way the study design has been set up. This flaw is unfortunately unavoidable given the type of data currently available. However,

[1] **#significance:** The poor results of the Rosenbaum Sensitivity Test show that the treatment effect is very sensitive to hidden bias; statistical significance is not even present at a gamma=1, where two units that appear to have the same propensity score should have the same propensity score in reality. This bias stems from flaws in the study design and data collection discussed below.

the number of observations dropped by the caliper offers insight into the kind of person who is likely to choose to take part in such a program. This is important for policy makers because while the current program may not be producing the kind of impact it hopes to achieve (in fact, it may be doing the opposite), this is not to say that it may not be able to do so in the future. The fact that these results are not replicable or externally valid may actually be a good thing. Community currency design is an nascent field with little long term empiracle evidence for its success.

Further stratification of the data pool as well as the treated unit pool reveals that there are observable differences between the income of subjects depending on where they live.

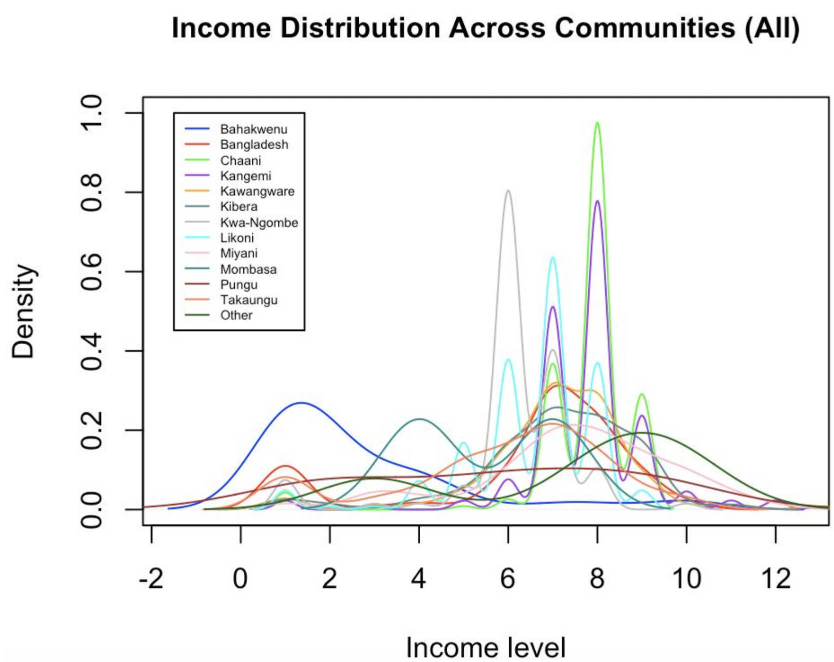

Figure 1: Total monthly income of all units depending on where they live. Distribution across the levels on the horizontal axis shows that there are clear differences in the wealth depending on the community under staudy. See Figure 2 below for income levels.

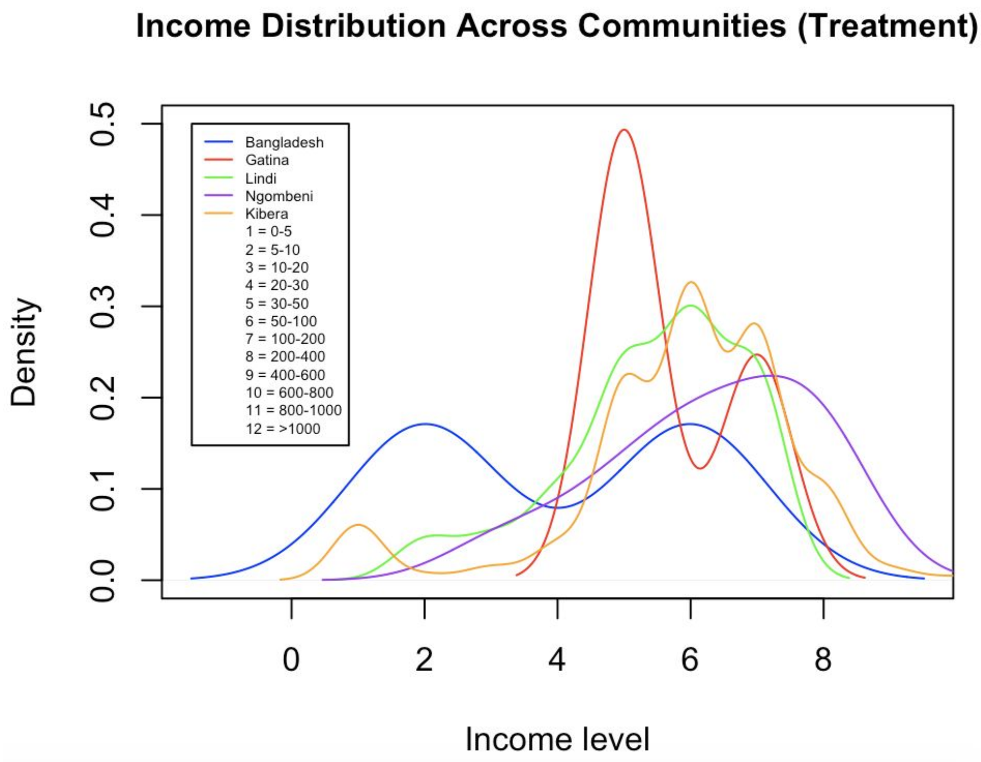

Figure 2: Total monthly income of community currency users depending on which community they live in. Bangladesh appears to a have more equally distibruted levels of wealth, while Ngombenim, Lindi and Kibera have a wealthier demographic.[2]

By analyzing the perceived benefit reported by community currency users, it appears that access to community-backed micro-credit is the real impact of the community currency program. However, the nature of the study design makes it impossible to test the causal effect of the program regarding credit because researchers have not yet measured this between treatment *and* control groups. It is therefore recommended that for future impact evaluations, the outcomes

[2] **#dataviz/#distributions:** A simple density plot is used to visualize the income distribution differences per community. The distirbutions skewed to the right show wealthier communities while the distribution strongly skewed to the left (Bangladesh slum) are much poorer on average. This visual is useful for the argument being made in the decision memo because it shows that the genetic matching results may be more affected by between-community differences than currently indicated by the combined data.

variables relevant to community currency users are also measured for non-users. This will enable crucial statistical methods needed for causal inference and may have serious implications for how policymakers view the role of commuity currency programs.

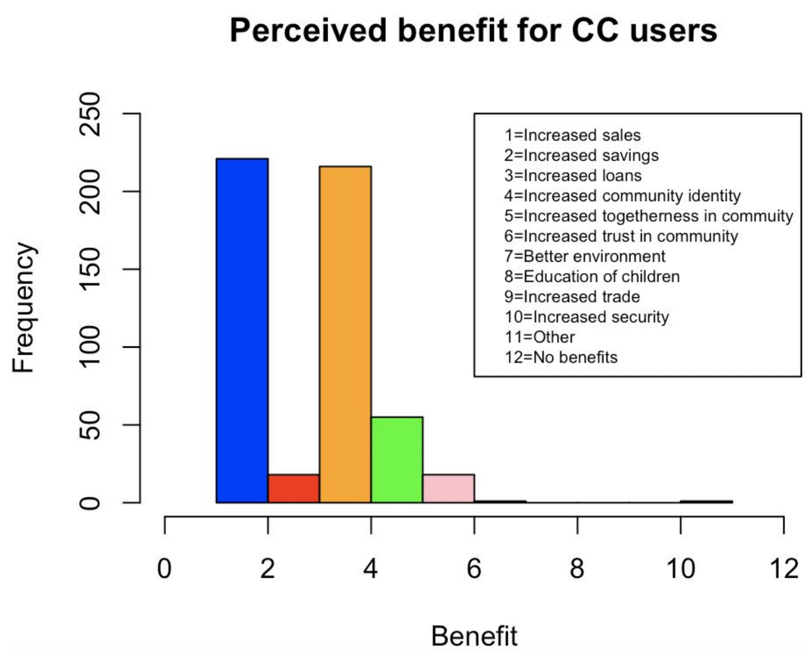

Figure 4: Perceived benefit of Grassroots Economics's community currency program by participants.

Conclusion

It appears that GE's program has so far been unsuccessful in improving the total income of program participants. However, evidence points to a potential impact area regarding access to micro-finance. The causal effect of the program is inconclusive due to incomplete data and an inappropriate studydesign. This initial baseline report should serve as a comparison for more rigourous evaluations in the future.

APPENDIX

See full Github code here:

https://github.com/RebeccaMqamelo/CS112/blob/master/CS112%20Final%20Project.R

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